Neural Network Based Fatigue Cracks Evolution

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Abstract. The crack density and crack growth rate are important parameters, which are used to describe the fatigue damage and predict the fatigue life of a material. There are many researches on the quantitative description of the fatigue cracks density and the crack growth rate, and several models are proposed, but these models cannot be widely used. In this paper, the BP network is used to describe the evolution of the fatigue crack density and the crack growth rate. It can be seen that the proposed method is feasible. The proposed method does not need to determine the interface between the long and short crack, and overcome the shortcoming of traditional models in which physical background of the parameters are uncertain, so it is difficult to determine in engineering.

1 Introduction

The crack density and crack growth rate are two important parameters that are used to describe the fatigue damage and predict the fatigue life of a material. The research on the quantitative description of the smooth sample surface fatigue crack density, evolution and the fatigue crack growth law has always been stressed. The evolution model of the fatigue crack density has ever been proposed successively from different perspectives by Suh [1], She [2], etc. Paris formula successfully describes the fatigue crack growth behavior of the crack object, which satisfies LEFM constrained conditions. Miller [3-6], Hobson [7], Polak [8] and Dowling [9] did a lot of work on the description of the fatigue short crack growth law and they posed their own models respectively. Due to the lack of the comparable experimental results and the unified standard, it is difficult to evaluate the advantages and disadvantages of these models. On the one hand, there are some parameters in these models and the physical significances of these parameters are unclear and hard to define practically; on the other hand, every model bases on a certain material structural characteristics, specific experiment conditions and it is proposed on a certain phase of the crack growth. As a result, their practical scope is constrained. Up to now, there is not extensively accepted the quantitative model of the crack evolution.

The neural network is a complicated nonlinear dynamic system with the ability of real time and pairing collective operation. In recent years, the neural network has been successfully applied in the field of automatic control, pattern recognition, and expert

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system, etc. But the research on applying the neutral network to describe the fatigue crack evolution law is rare in the literature. There are four main types of the neutral network, which are multilayer forward, feedback, self-organizing and random network. Among them, the multilayer forward network is fit to process a large amount of discrete, noise-bearing and incomplete data collection, and the law can be extracted from the process without analytical expression. It is a good tool to process the fatigue crack evolution experimental data and describe the fatigue crack evolution behavior.

2 Factors Affecting the Fatigue Crack Evolution

Many factors can affect the fatigue crack evolution of the material. These factors include the material features, load features and environment, etc. The following equation can describe the evolution of the smooth sample surface fatigue crack density:

$$n(N) = f_n(K_c, d, \Delta\sigma, R, C, \cdots) \tag{1}$$

where n is the crack density; N is the load cyclic frequency; K_c is the fracture toughness of the material; d is the microstructure scale of the material; $\Delta\sigma$ is the applied stress amplitude; R is the stress proportion; C is the environmental temperature.

Only through experiments can we know how these factors affect the fatigue crack density. At present, the influence of a few factors can be studied through experiments. In addition, even if the experiment studies the function of every factor, it is difficult to embody the results on the quantitative model. For example, the model of AlSi304 stainless steel fatigue crack density under the temperature of 538° C set by Suh, Lee, Kang, Ahn, and Woo [1] only embodies the function of the stress amplitude.

Concerning the problem of the fatigue crack growth, it is widely thought that the growth behavior of the long crack is different from that of the short crack and models set up to describe their laws. It is reasonable to apply Paris formula to describe the long fatigue crack. In the improved Paris formula, the influence of the stress proportion R is considered, which makes the result of the prediction more conform to the reality. The behavior of the short fatigue crack is very complicated. Besides the affecting factors of the long crack, the microstructure of the material, such as, the crystallite dimension, the shape and orientation of the defect, the local directional properties and so on will affect the growth of the short crack. Miller [3-6], Hobson [7], Polak [8] and Dowling [9] did a lot of work to describe the evolution law of the fatigue short crack and all of them set up their own models.

It is difficult to actually define the boundary between the long crack and the short crack, so the above-mentioned model can hardly be applied practically. With the aid of the neural network, the long crack and the short crack can be united and described, the general expression is:

$$\frac{\mathrm{d}a}{\mathrm{d}N} = f_a(K_c, d, \Delta K \text{ or } \Delta\sigma, a, R, C, \cdots) \tag{2}$$

where ΔK is the stress intensity factor variation amplitude; $\Delta\sigma$ is the stress variation amplitude; R is the stress proportion; a is the length of the crack.

The factors which affect the evolution law of the fatigue crack are: the crack ductility of the material, the size of the microstructure, the stress variation amplitude, the length of the crack, the stress proportion and environmental temperature, etc. Among them, the performance of the material and the applied stress amplitude are more important.

3 The Neural Network Model of the Fatigue Crack Evolution

To extract the evolution law of the fatigue crack from the fatigue experimental data through the application of the BP network, at first, the network structure should be defined according to the practical problem, that is, the number of the neuron in the input, output and hidden layer. And then, train the network repetitively by way of the samples made up of the experimental data and the BP algorithm until it converges, so far, the establishment of the model accomplishes and the working phase begins.

3.1 Smooth Sample Surface Fatigue Crack Density

Eq. (1) shows that the crack ductility of the material K_c, the size of the microstructure of the material d, the applied stress amplitude $\Delta\sigma$, the stress proportion R and the environmental temperature C will affect the number of the crack at a certain recycle times in varying degree. For this reason, both the above-mentioned parameters and loaded cyclic numbers are regarded as the input of the network, the number of the neuron in the input layer corresponds to it. The unit of the output layer corresponds to the crack density n. To the experiments on the same material with the same stress proportion and environmental conditions, the unit of the input layer of the network corresponds to the stress amplitude and loaded recycle times. 1Cr18Ni9Ti smooth sample surface fatigue experiment is carried out on the MTS material fatigue experimental machine. The stress control is adopted, the monopodium tensile and compressive stress proportion is $R=-1$, the loaded frequency is 2.0Hz, the experimental environment is indoor temperature 17° C and the medium is air. The replication method is adopted to observe the evolution of the sample surface crack. At first, duplicate the change of the surface state in the sample fatigue process discontinuously, and then, put the replication thin film under the optical microscope to amplify to many times and observe it, the observing order is inversed. When replicating, it is guaranteed that the sample is proceeding under the bearing of 10kN tensile load, moreover, two roughly symmetrical plates are duplicated every time in order to ensure that the interested area is not left out. Table 1 shows the experimental data of 1Cr18Ni9Ti smooth sample surface fatigue crack density.

Double hidden layers are taken; all the units of the hidden layers are five. When training, the learning factor η=0.9, the inertia term coefficient α=0.7 are taken. Through 30 000 learning, the network converges; the population error is 3.4×10^{-5}. The selection of the number of the hidden layer, the learning factor and the inertia term coefficient is empirical. But they just affect the speed of convergence, not the result of convergence.

Table 1. Experimental data of 1Cr18Ni9Ti smooth sample surface fatigue crack density

σ_a (MPa)	N/N_f n	N/N_f n	N/N_f n	N/N_f n	N/N_f n	N/N_f n	N/N_f n	N/N_f n
340	0.981 203	0.921 41	0.809 17	0.698 4	0.587 1			
350	0.965 302	0.89 276	0.816 194	0.742 118	0.668 57	0.594 2	0.519 1	0.445 1
370	0.913 219	0.783 122	0.652 68	0.522 45	0.391 4	0.261 1		
320	0.966 82	0.875 47	0.783 27	0.692 15	0.646 2	0.601 2	0.556 1	
310	0.936 73	0.869 40	0.803 25	0.736 12	0.669 2	0.602 2	0.535 2	

3.2 Smooth Sample Surface Fatigue Crack Growth Rate

Comparing Eq. (1) with (2), the results show that all the parameters, which affect the fatigue crack density, will also affect the fatigue crack growth rate, in addition, the growth rate of the crack varies with its length. Consequently, to the experiments to the same material with the same stress proportion and environmental conditions, the input units of the network corresponds to the stress amplitude and the crack length; the output unit corresponds to the crack growth rate. Table 2 shows the experimental data (training sample) of 1Cr18Ni9Ti smooth sample surface crack growth rate.

Table 2. Experimental data (training sample) of 1Cr18Ni9Ti smooth sample surface crack growth rate

σ_a (MPa)	a da/dN	a da/dN	a da/dN	a da/dN	a da/dN	a da/dN	a da/dN	a da/dN	a da/dN	a da/dN
340	25 0.034	64 0.052	180 0.0928	520 0.272	660 0.112	1640 0.784	4200 3.776			
350	4 0.0053	16 0.016	24 0.0107	88 0.0853	200 0.0747	280 0.1067	580 0.4	1080 0.6667	2080 1.3333	
370	45 0.075	88 0.0717	192 0.1733	224 0.0533	560 0.56	2200 2.7333				
320	10 0.004	12 0.0008	12 0.0001	15 0.0012	32 0.0068	68 0.0144	92 0.0096	140 0.0096	400 0.052	1240 0.168
310	5 0.001	12.5 0.0015	17.5 0.001	20 0.0005	60 0.008	60 0.0001	84 0.0048	112 0.0056	160 0.0096	220 0.012
400	24 0.0274	68 0.176	88 0.16	112 0.192	140 0.224	180 0.32	200 0.16	200 0.0001	460 1.04	580 0.48

The hidden layer of the network is double-layer; the number of the neurons in the first and second hidden layer is 5 and 7 respectively. In the training process, the learning factor $\eta = 0.9$, the inertia coefficient $\alpha = 0.7$ are taken. Through 30 000 learning, the total error is 1.89×10^{-4}.

Before training the network, the normalization of the samples must be carried out, that is, adjusting all the sample values to the interval [0,1].

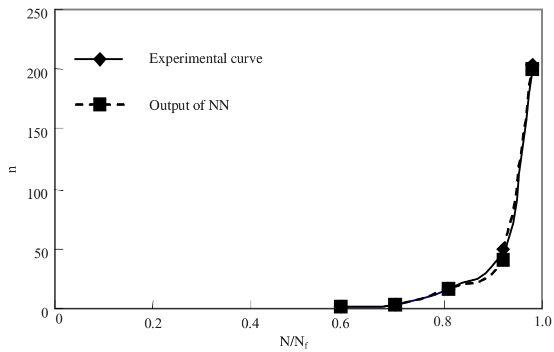

Fig. 1. Curve of 1Cr18Ni9Ti material smooth sample surface crack quantity

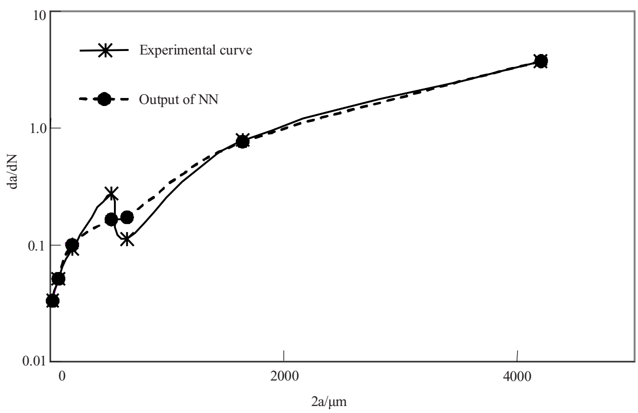

Fig. 2. Curve of 1Cr18Ni9Ti material smooth sample surface crack growth rate

Figure 1 and 2 show the experimental curve of 1Cr18Ni9Ti material smooth sample surface crack quantity and the crack growth rate and the neural network model calculating curve under the acting of the stress amplitude $\alpha = 340\text{MPa}$ respectively (there is a conspicuous depression on the experimental curve in Figure 3, which is caused by the deficiency of the data and that the measured data is random to certain extent). The figures reflect the experimental curve and the network output curve of the crack quantity and the crack growth rate are identical.

4 Conclusions

The neural network is a complicated nonlinear dynamic system with the ability of real time and pairing collective operation. It combines calculation and storage into one. Recently the neural network has been applied in many fields and the attempt is successful. The multilayer forward network is suitable to process a large number of discrete, noise-bearing and incomplete data collection, from which the law can be extracted without analytical expression. This is a good tool to process the fatigue crack evolution experimental data and describe the fatigue crack evolution behavior.

When applying the neural network to describe the fatigue crack growth rate, it is unnecessary to distinguish the long and short crack. Therefore, it overcomes the shortcomings of traditional models in which it is difficult to determine the interface between the long and short crack, and the physical background of the parameter in analytical models is uncertain and hard to define practically. The reason of the method is very simple and it is fit for the engineering application.

A network can be trained with the fatigue crack evolution experimental data to different materials and under different stress levels, thus, a data base of the material fatigue crack evolution can be set up. The similar method can be adopted to process the experimental data of the material performance.

This paper adopts the neural network to describe the evolution laws of the fatigue crack density and crack growth rate. The analysis to the examples has proved that the method is feasible.

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